Kyrlwob

1.1

```
[1]: import numpy as np import matplotlib.pyplot as plt import pandas as pd
```

1.2

```
[2]: dataset = pd.read_csv('/content/blood.csv')
  dataset.head()
```

```
[2]:
        Recency (months) Frequency (times) Monetary (c.c. blood)
                                                                      Time (months)
     0
                       2
                                          50
                                                               12500
                                                                                  98
     1
                       0
                                                                3250
                                          13
                                                                                  28
     2
                       1
                                          16
                                                                4000
                                                                                  35
                       2
     3
                                          20
                                                                5000
                                                                                  45
     4
                        1
                                          24
                                                                                  77
                                                                6000
```

whether he/she donated blood in March 2007

```
0 1
1 2 1
3 1
4 0
```

```
]]
     2
           50 12500
                       98]
13 3250
     0
                       28]
[
     1
           16 4000
                       35]
[
     2
           20 5000
                       45]
     1
           24 6000
                       77]]
```

[1 1 1 1 0]

1.3

```
[4]: # from sklearn.preprocessing import Imputer
# imputer = Imputer(missing_values = 'NaN', strategy = 'mean', axis = 0)
# imputer = imputer.fit(X[:, 1:3])
# X[:, 1:3] = imputer.transform(X[:, 1:3])
# print(X)
```

1.4

1.4.1 (LabelEncoder)

```
[5]: # from sklearn.preprocessing import LabelEncoder
# labelencoder_y = LabelEncoder()
# print(" ")
# print(y)
# y = labelencoder_y.fit_transform(y)
# print(" ")
# print(y)
```

1.4.2 OneHotEncoder

```
[[0.0000000e+00 0.0000000e+00 1.0000000e+00 1.6534920e+05 1.3689780e+05 4.7178410e+05]
[1.0000000e+00 0.0000000e+00 0.0000000e+00 1.6259770e+05 1.5137759e+05 4.4389853e+05]
[0.0000000e+00 1.0000000e+00 0.0000000e+00 1.5344151e+05 1.0114555e+05 4.0793454e+05]
[0.0000000e+00 0.0000000e+00 1.0000000e+00 1.4437241e+05 1.1867185e+05 3.8319962e+05]]
```

D:\ml\Anaconda3\lib\site-packages\sklearn\preprocessing_encoders.py:363: FutureWarning: The handling of integer data will change in version 0.22. Currently, the categories are determined based on the range [0, max(values)], while in the future they will be determined based on the unique values. If you want the future behaviour and silence this warning, you can specify

```
warnings.warn(msg, FutureWarning)
    D:\ml\Anaconda3\lib\site-packages\sklearn\preprocessing\ encoders.py:385:
    DeprecationWarning: The 'categorical_features' keyword is deprecated in version
    0.20 and will be removed in 0.22. You can use the ColumnTransformer instead.
      "use the ColumnTransformer instead.", DeprecationWarning)
    1.5
                                                             ,
[6]: X = X[:, 1:]
    print(X[:4,:])
    ГΓ
        50 12500
                    981
     Γ
        13 3250
                    281
     Γ
        16 4000
                    35]
     Γ
        20 5000
                    4511
    1.6
[7]: # from sklearn.cross validation import train test split
    from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, __
     →random state = 0)
    1.7
[8]: from sklearn.linear_model import LinearRegression
    regressor = LinearRegression()
    regressor.fit(X_train, y_train)
[8]: LinearRegression()
    1.7.1
[9]: y_pred = regressor.predict(X_test)
    print(y_pred)
    0.2916319
      0.21280578 0.2916319
                            0.13418344 0.41216059 0.21143328
                                                              0.17191833
      0.27444263 0.41394065 0.342031
                                        0.12253813 0.22999506
                                                              0.17685096
      0.07966684 0.27149385 0.12075807 0.25567708 0.228215
                                                              0.26416982
      0.2060931
                 0.3434035
                            0.27444263 0.42462102 0.19404023
                                                              0.13103088
                                                              0.26416982
      0.3914112
                 0.152949
                            0.08953209 0.2422517 -0.0558635
      0.20253298 0.19999175 0.22999506 0.20253298 0.25567708 0.19938041
```

In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integers, then you can now use the OneHotEncoder directly.

"categories='auto'".

```
0.46194835 0.26635744 0.2060931
                                 0.24026786 0.228215
                         0.28176665
0.18910761 0.28176665 0.07590294 0.30210849 0.13774357 0.24026786
0.09665234 0.27444263 0.27820653 0.22725005 0.26416982 0.26416982
0.37640954 0.134591
0.27444263 0.19088767 0.10158496 0.26416982 0.32265411 0.22999506
0.34045472 0.28847934 0.34497978 0.31833282 0.26101726 0.0725466
0.3123813
        0.42578974 -0.00251562 0.3951751
                         0.27444263 0.3123813
                                         0.3509313
0.19404023 0.25567708 0.21280578 0.06405385 0.16657815 0.25567708
0.285123
        0.16520565 0.27444263 0.17685096 0.16006924 0.21280578
        0.3641529
0.33984338 0.20431304
0.30190471 \quad 0.26416982 \quad 0.30114355 \quad 0.30566861 \quad 0.34360728 \quad 0.25745714
0.28491922 0.29341196 0.209857
                         0.30902496 0.09309221 0.2060931
0.16835821 0.2384878
                0.29046318  0.23355518  0.28491922  0.30922873
0.1567129
       0.26416982 0.23355518 0.15986546 0.21478962 0.20253298]
```

```
[]: import statsmodels.formula.api as sm
X = np.append(arr = np.ones((50, 1)).astype(int), values = X, axis = 1)
X_opt = X[:, [0, 1, 2, 3, 4, 5]]
regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
regressor_OLS.summary()
```

[]: <class 'statsmodels.iolib.summary.Summary'>

OLS Regression Results

===========	===========		=========
Dep. Variable:	у	R-squared:	0.951
Model:	OLS	Adj. R-squared:	0.945
Method:	Least Squares	F-statistic:	169.9
Date:	Thu, 01 Sep 2022	Prob (F-statistic):	1.34e-27
Time:	17:45:14	Log-Likelihood:	-525.38
No. Observations:	50	AIC:	1063.
Df Residuals:	44	BIC:	1074.
Df Model:	5		

Covariance Type: nonrobust

=======				=======	========	========
	coef	std err	t	P> t	[0.025	0.975]
	F 040 +04	6004 000	7 004	0.000	2 60 .04	C 4 + 0.4
const	5.013e+04	6884.820	7.281	0.000	3.62e+04	6.4e+04
x1	198.7888	3371.007	0.059	0.953	-6595.030	6992.607
x2	-41.8870	3256.039	-0.013	0.990	-6604.003	6520.229
x3	0.8060	0.046	17.369	0.000	0.712	0.900
x4	-0.0270	0.052	-0.517	0.608	-0.132	0.078

x5	0.0270	0.017	1.574	0.123	-0.008	0.062
Omnibus: Prob(Omnibus): Skew: Kurtosis:		14.782 0.001 -0.948 5.572	Jarque-B Prob(JB)	era (JB):		1.283 21.266 2.41e-05 1.45e+06

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.45e+06. This might indicate that there are strong multicollinearity or other numerical problems.

```
[]: X_opt = X[:, [0, 1, 3, 4, 5]]
regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
regressor_OLS.summary()
```

[]: <class 'statsmodels.iolib.summary.Summary'>

Dep. Vari	iable:		У	R-sq	uared:		0.951
Model:			OLS	Adj.	R-squared:		0.946
Method:		Least So	quares	F-st	atistic:		217.2
Date:		Thu, 01 Sep 2022			(F-statist	ic):	8.49e-29
Time:		17	45:18	Log-	Likelihood:		-525.38
No. Obser	rvations:		50	AIC:			1061.
Df Residu	uals:		45	BIC:			1070.
Df Model:	:		4				
Covariand	ce Type:	non	robust				
=======	coef	std er	 :	====== t	P> t	[0.025	0.975]
const	5.011e+04	6647.87)	 7.537	0.000	3.67e+04	6.35e+04
x1	220.1585	2900.53	3	0.076	0.940	-5621.821	6062.138
x2	0.8060	0.046	3 1	7.606	0.000	0.714	0.898
x3	-0.0270	0.05	2 -	0.523	0.604	-0.131	0.077
x4	0.0270			1.592	0.118	-0.007	0.061
Omnibus:		:	 14.758	Durb:	======= in-Watson:		1.282
Prob(Omni	ibus):		0.001	Jarq	ue-Bera (JB):	21.172
Skew:		-	-0.948	_			2.53e-05
Kurtosis	:		5.563	Cond	. No.		1.40e+06

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.4e+06. This might indicate that there are strong multicollinearity or other numerical problems.

```
[]: X_opt = X[:, [0, 3, 4, 5]]
regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
regressor_OLS.summary()
```

[]: <class 'statsmodels.iolib.summary.Summary'>

OLS Regression Results

0-2 100-020-02						
Dep. Variable:	у	R-squared:	0.951			
Model:	OLS	Adj. R-squared:	0.948			
Method:	Least Squares	F-statistic:	296.0			
Date:	Thu, 01 Sep 2022	Prob (F-statistic):	4.53e-30			
Time:	17:45:23	Log-Likelihood:	-525.39			
No. Observations:	50	AIC:	1059.			
Df Residuals:	46	BIC:	1066.			
Df Model:	3					
Covariance Type:	nonrobust					
=======================================	:==========		===========			
			_			

=======		========		=======	========	
	coef	std err	t	P> t	[0.025	0.975]
const	5.012e+04	6572.353	7.626	0.000	3.69e+04	6.34e+04
x1	0.8057	0.045	17.846	0.000	0.715	0.897
x2	-0.0268	0.051	-0.526	0.602	-0.130	0.076
x3	0.0272	0.016	1.655	0.105	-0.006	0.060
========	========	========		=======	========	=======
Omnibus:		14.8	838 Durbin	-Watson:		1.282
Prob(Omnib	ous):	0.0	001 Jarque	-Bera (JB)	:	21.442
Skew:		-0.9	949 Prob(J	B):		2.21e-05
Kurtosis:		5.	586 Cond.	No.		1.40e+06

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.4e+06. This might indicate that there are strong multicollinearity or other numerical problems.

regressor_OLS.summary()

[]: <class 'statsmodels.iolib.summary.Summary'>

OLS Regression Results

=======			======				========
Dep. Varia	able:		У	R-sqı	uared:		0.950
Model:			OLS	Adj.	R-squared:		0.948
Method:		Least Squ	ares	F-sta	atistic:		450.8
Date:	-	Thu, 01 Sep	2022	${\tt Prob}$	(F-statistic)):	2.16e-31
Time:		17:4	5:28	Log-I	Likelihood:		-525.54
No. Observ	ations:		50	AIC:			1057.
Df Residua	als:		47	BIC:			1063.
Df Model:			2				
Covariance	e Type:	nonro	bust				
=======			======				
	coef	std err		t	P> t	[0.025	0.975]
const	4.698e+04	2689.933	 17.	. 464	0.000	4.16e+04	5.24e+04
x1	0.7966	0.041	19.	. 266	0.000	0.713	0.880
x2	0.0299	0.016	1.	.927	0.060	-0.001	0.061
========			======	=====			========

-0.939 Prob(JB):

0.001

14.677 Durbin-Watson:

Jarque-Bera (JB):

1.257

21.161

2.54e-05

Warnings:

Omnibus:

Skew:

Prob(Omnibus):

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 5.32e+05. This might indicate that there are strong multicollinearity or other numerical problems.

[]: <class 'statsmodels.iolib.summary.Summary'>

OLS Regression Results

Dep. Variable:	у	R-squared:	0.947
Model:	OLS	Adj. R-squared:	0.945
Method:	Least Squares	F-statistic:	849.8
Date:	Thu. 01 Sep 2022	Prob (F-statistic):	3.50e-32

059.
063.
975]

	coef	std err	t	P> t	[0.025	0.975]
const x1	4.903e+04 0.8543	2537.897 0.029	19.320 29.151	0.000	4.39e+04 0.795	5.41e+04 0.913
Omnibus: Prob(Omnibu Skew: Kurtosis:	ıs):	0.):	1.116 18.536 9.44e-05 1.65e+05

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.65e+05. This might indicate that there are strong multicollinearity or other numerical problems.